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Socio-economic impacts of low-volume roads using a mixed-method approach of PCA and Fuzzy-TOPSIS

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Abstract: The present study proposes a novel mixed-method approach to ascertain and explore the socio-economic indicators, which help in assessing the impacts of the construction of rural roads. Rural road infrastructure often has direct or indirect socio-economic impacts (SEIs) on the target population. Assessment of SEIs poses a wide range of challenges due to their multi-dimensional nature of various factors and their qualitative and quantitative evaluation process. Thus, the present study suggests a unique mixed-method approach to integrate multivariate techniques under a multi-criteria fuzzy framework. The applicability of this approach is demonstrated by employing a case study of roads constructed under the Pradhan Mantri Gram Sadak Yojana (PMGSY) in the Jhunjhunu district of Rajasthan, India. The findings of the study analysed a total of 33 sub-criteria associated with five main indicators, impacted by the construction of PMGSY roads. Sub-criteria contributing to education facility and quality of neighbourhood have been found as the most significant effects. The results of the analysis presented in this study would benefit the respective State Governments to achieve sustainable rural development.

1. INTRODUCTION

Witnessing limited redistributive channels, governments of developing countries, and aid donor agencies look forward to achieving distributional objectives by facilitating income opportunities, basic health, and educational facilities among the rural population through road interventions. These interventions facilitate efficiency benefits by encouraging rural households in taking up new opportunities that help them in relieving their well-being constraints (Abur, Ademoyewa, & Damkor, 2015; Wagale, Singh, & Sarkar, 2019).

Globally road systems are recognized as significant contributors to the social and economic development of a nation. In case of rural areas, roads improve mobility and provide access to basic services and market centres. In recent times, most of the developing countries have emphasized improving road infrastructure for rural areas, and India has also taken a great lead to develop such infrastructures. The Government of India initiated a major rural road development plan in the country, known as Pradhan Mantri Gram Sadak Yojana (PMGSY), in the year 2000. The objective of this program is to connect rural habitations having a population of 250 persons and above (for desert and hilly regions) by all-weather roads to the nearest village or market centres. The scheme is targeted for poverty alleviation and the development of rural habitations thereby enhancing their socio-economic status.

Developed road infrastructure in context with rural areas (villages) has a significant impact on the target population. They provide new avenues and employment opportunities for rural inhabitants (Riverson, Gaviria, & Thriscutt, 1991) and bring out economic growth with poverty alleviation (Lebo & Schelling, 2001; Banister & Berechman, 2003). Rural roads generate market activities due to reduced transport costs, as well as foster linkages to economic centres which help rural habitants to enhance their agricultural production. Rural roads also stimulate non-farm activities along with alteration in land use, and crop diversification (Van de Walle, 2009). Better rural roads enhance social outcomes by facilitating access to social services such as education and health facilities. This is actualized in terms of an increase in the number of school-going children due to the reduction in travel time to reach the facility (Khandker, Bakht, & Koolwal, 2009). The same holds in the case of access to a health facility, individuals can get medical treatments at the first call due to good road connectivity (Porter, 2012; Tunde & Adeniyi, 2012; Kanuganti et al., 2017; Wagale & Singh, 2019). Thus transportation and road infrastructure play an important role in the overall development of a rural town or urban city (Jittrapirom & Jaensirisak, 2020).

Despite consensus on how rural roads are important to enhance the quality of life in the rural areas, surprisingly, there is little evidence in the literature that captures the size and nature of benefits in a comprehensive way. Indeed, there are few rigorous studies, which assess the benefits of rural roads credibly, but they still lag to capture distributional impacts induced by them. Traditionally, the planning of roads and their investment decisions have been prioritized based on cost-benefit assessments. These studies attempted to assess rural road investment by considering the savings incurred in terms of vehicle operating cost and reduction in travel time. However, in case of developing countries where the traffic in rural areas is too low, the application of conventional methods such as cost and benefit analysis cannot be relied completely upon (Van de Walle, 2009).

Moreover, rural road infrastructure is necessity-based, i.e., they are constructed not just for the sole purpose of travel but also to improve the socio-economic condition of the target population. At the same time, the target population served by these roads is diverse in terms of socio-economic backgrounds with different necessities, which makes the task of assessment of rural road investment complex. Also, some of the impacts may be direct or indirect (positive or negative) which are difficult to be captured by using conventional cost-benefit analysis (Grootaert & Calvo, 2002). The classical cost-benefit analysis, then, needs to be replaced by a socio-economic impact assessment methodology (SEIA) to get a measure of expected benefits and costs to different groups. Assessment of impacts adds up as an input to the decision-makers by providing better information on both positive and negative impacts of delivered infrastructure. Impact evaluation is an important tool in policy-oriented executions (Asomani-Boateng, Fricano, & Adarkwa, 2015; Ehrlich & Ross, 2015).

In recent times, studies have been performed to understand the impacts of rural road construction using different impact evaluation techniques. But it has been observed that these studies faced difficulties in assessing the magnitude of the impacts due to the underlying problem of endogeneity as well as identification of proper key performance indicators, which play major roles in the impact evaluation process of infrastructure development in a comprehensive manner (Baker, 2000; Rowan, 2009). The most common shortcomings of previous studies are the selection of appropriate indicators and the target population, which are influenced by the placement of the rural roads as well as its outcomes. A better evaluation process of the impacts requires proper identification of the indicators (i.e., data), which are of potential importance and are affected directly or indirectly by the improvements in the roads.

Appropriate impact indicators form the basis of sustainability planning and comprehensive management of road infrastructure. They play a vital role in establishing a baseline of impacts and help in identifying their trends. Impact indicators significantly influence the assessment process if not selected appropriately. Thus, the selection of key impact performance indicators becomes a vital challenge as they provide useful information on the goals achieved if the road infrastructures are delivered. As rural roads cause various impacts on economic, social, and environmental aspects of the target population, employing a single indicator to assess the impact may not be sufficiently adequate; rather, it can be well addressed by a set of indicators. Thus, comprehensive impact assessment for economic, social, and environmental aspects can collectively be well defined in terms of key indicators such as an increase in individual/household income, availability of jobs, income diversification, etc. (Litman, 2007).

Indicators selected, are considered to have many uses: they can help in identifying possible trends, predicting impacts, assessing intervention based on performance goals, and evaluating the effects of the intervention on an identified section of the population (target population) (Nirban et al., 2003). Therefore, it is important to select indicators carefully that reflect the overall aim of the scheme or intervention (Vyas & Kumaranayake, 2006). Also, indicators selected are often required to be realistic from viewpoint of availability of data, their ability to be perceived, and convenience in decision making. Hence, it is necessary to understand the perspectives and limitations of each indicator. However, there exists a tension between suitability and comprehensiveness while identifying indicators. If small indicators set are selected, it may overlook important impacts. It possibly may distort the overall outcome, though convenient to use considering the availability of data, whereas, a larger set may not be cost-effective and will be difficult to quantify (Morimoto, 2013).

Currently, no standardized techniques are available to identify a set of indicators for a comprehensive assessment of the impacts of road infrastructure. They are generally developed based on experience learned to tackle a particular problem and the background of the study areas. Therefore, it is essential to develop a methodology that can help to recommend appropriate indicator sets from viewpoint of sustainable planning and evaluation of best practices. Thus, keeping this in view, this study develops a novel methodology to explore important performance key indicators by considering ex-post evaluation conditions for newly constructed all-weather rural roads.

The novel methodology of the present study is based on the concept of mixed-method design (i.e., concurrent triangulation design), where the findings of both quantitative and qualitative techniques are compared to cross-validate the outcome. In the present study, principal component analysis (PCA) which considers quantitative assessment is compared with fuzzy multi-criteria decision-making (MCDM), which contemplates qualitative assessment. A case study of rural roads constructed under the PMGSY scheme in the Jhunjhunu district of Rajasthan state of India is considered to illustrate the effectiveness of the proposed methodology. To set the flow of the study, the paper is divided into five sections.

Section 1 of the paper introduces the research problem and its need to be resolved. It also discusses some of the generic issues that curtail the selection process of indicators in context with impacts instigated due to improvements in rural roads. Section 2 addresses the case study along with criteria/indicator selection and data collection. Next, section 3 discusses the proposed methodological approach as well as the steps followed in the evaluation. Section 4 briefly analyses the results and findings of the proposed methodology, while section 5 concludes the study by considering the assessment and findings of the proposed study.

2. STUDY AREA AND DATA

2.1 Case study

The present study follows the ex-post approach in selecting road stretches and identifies them based on their geographical location and the size of the target population. The study also considers the year of their execution in selecting road stretches (i.e., a newly laid road does not instigate impacts immediately, except for a few benefits. On the other hand, when the road ages and becomes a part of the structure in the village, it is difficult for the inhabitants to appreciate the impacts). The aim is to have a dataset with reduced errors (biases associated with the perception of rural inhabitants). Thus, considering these aspects present analysis selects road stretches in four different blocks, viz., Buhana, Jhunjhunu, Khetri, and Surajgarh of Jhunjhunu district of Rajasthan state, India. The road stretches have been constructed in the year 2013-2014 under the PMGSY scheme. *Figure 1* depicts different blocks in the Jhunjhunu district along with through-routes employed for the study. A total of 19 new connectivities are considered for the assessment. These connectivities have been directly serving a total population of 6785 persons.

2.2 Selection of criteria/indicators

Assessing rural road projects and their impacts is an important aspect from the viewpoint of the welfare of the community. The impacts of the construction of rural roads are many and some of them are not attained immediately. Some of them are visible immediately as quick wins, others might be evaluated on a mid-term basis and a few important impacts might be required to assess on a long-term basis to achieve sustainable development. Thus, quantification of these impacts becomes quite complicated due to uncertainty associated with different stages of the decision-making process at different time intervals. The selection of appropriate criteria for assessing the impacts must be done carefully. The selected criteria should account for the change which is both qualitative and quantitative and should be competent enough to account for the impacts in a comprehensive manner. In consideration of these aspects, the study follows a systematic method in selecting important criteria as illustrated in *Figure 2*. Initially, the study focuses on the available scientific literature which is followed by opinions of the expert group. The expert group consisted of a team of five members belonging to educational and research institutes, government organizations, especially those authorities who are working in the field of rural development schemes. Moreover, a preliminary survey has been done in a few selected habitations to get direct feedback from the rural inhabitants, and accordingly, a set of 33 sub-criteria are identified under five main criteria/indicators. *Table 1* below depicts the SEIA criteria considered for the study.

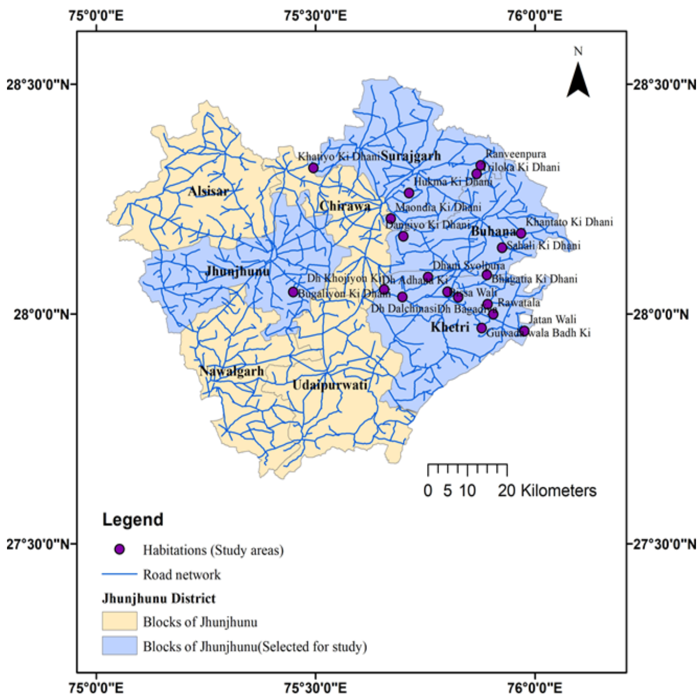

Figure 1. Block boundaries showing through routes in Jhunjhunu district, Rajasthan

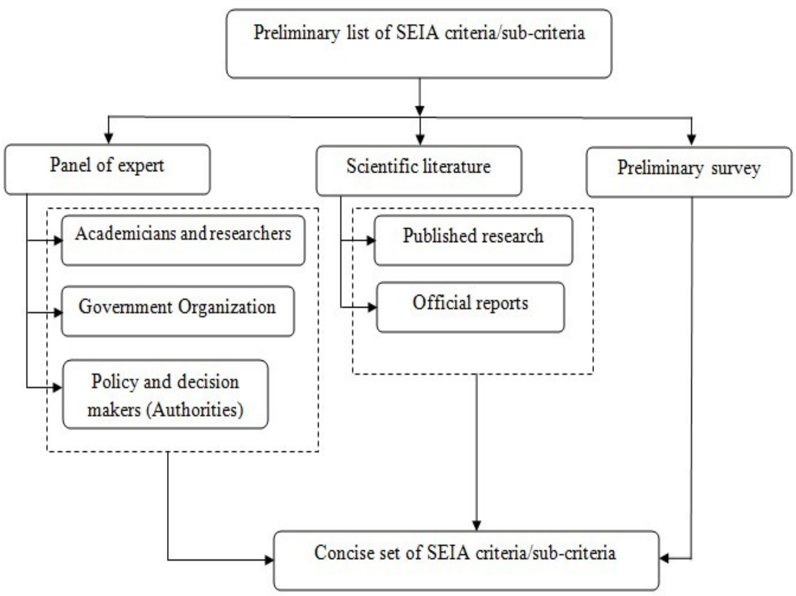

Figure 2. The Process followed for SEIA criteria selection

Table 1. SEIA criteria with sub-criteria employed in the study

Criteria/Indicators				
Transport facility	Income status	Health facility	Education facility	Quality of neighbourhood (social environment)
Travel time using public transportation (TTPUB)	Individual income (II)	Use of health facility (HFU)	Literacy rate of male (EMLR)	Ownership of personal phone (QPPO)
Travel time using private transportation (TTPVT)	Household income (HI)	Availability of health clinic (HCA)	Literacy rate of female (EFLR)	Ownership of television (QTVO)
Public transportation units (PUBTU)	Income of self-employed from agriculture (ISA)	Availability of primary health center (PHCA)	Percent of male children attending schools (EMAS)	Livability (QL)
Private transportation units (PVTTU)	Income of wage labour from agriculture (IWA)	Access to the mode of transport for health facility (HAM)	Percent of female children attending schools (EFAS)	Involvement in social-gathering within the village (QSGIV)
Frequency of public transportation (PUBF)	Income from livestock (IL)	Travel time to reach health facility (HTT)	Access to the mode of transport for education facility (EAM)	Involvement in social-gathering outside the village (QSGOV)
Public transportation cost (PUBTC)	Income of unskilled labour from agriculture (IUA)	Health status (anthropometric measures up to adolescent age) (HSANT)	Travel time to reach education facility (ETT)	
Private transportation cost (PVTTC)	Income of unskilled labour from non-agriculture (IUNA)		Availability of preschools (PRESA)	
			Availability of primary schools (PRISA)	

2.3 Data collection

The collection of data and its assessment are essential in the decision-making process as well as in predicament elucidation (Hair et al., 1995). One of the key mechanisms to be employed for collecting necessary data for impact assessment study is through a focus-group survey (perceptions of the target population). The data for the present study is collected from a total of 19 habitations connected by PMGSY roads in the Jhunjhunu district of Rajasthan State, India. The sample size required for data collection is 259 persons, considering the total population (6,785 persons) to be served from these habitations and with a 90% confidence interval and 5% of marginal error. Thus, 19 Focus-groups with 14 participants per group were identified from the respective habitations. The participants consisted of government and private employees, self-employed persons (especially, farmers and traders), and students (age 16 to 45 years). The focus group consisted of 66 % of males and 34 % of female participants. A preliminary survey has been conducted before the final survey to avoid potential risks (indulgence of error) associated with the overall survey process.

The focus group surveys have been conducted in April–May 2016. All discussions are based on a questionnaire, designed after a comprehensive study and is broadly divided into five sections, viz., impacts on transport facility, income status, education facility, health facility, and quality of neighbourhood (social environment). The perceptions of focus groups are collected to capture the necessary information required on how the criteria have impacted the inhabitants and to consider their level of satisfaction. The level of satisfaction captured for each of the indicators is gauged on a linguistic scale ranging from highly satisfied to extremely dissatisfied scale. The scores are assigned from 1 to 5 (5 being highly satisfied and 1 being extremely dissatisfied). Further, the data collected is normalized and is re-scaled to [0, 1] for ease of assessment using the min-max normalization technique as shown in *Equation 1,* thus, linearly transforming the data as described by Phogat and Singh (2013). Before the commencement of formal data collection, the enumerators had a general discussion with the participants about the habitation and their lifestyle. This facilitated the formal data collection process with ease and comfort between enumerators and participants. The authenticity of data has been ensured with participants through feedback at the end of group discussions. The distribution of data (descriptive analysis) collected through focus group discussion representing the condition after the construction of rural roads is presented in Appendix II.

$$a_{norm} = \frac{(a_i - a_{\min})}{(a_{\max} - a_{\min})}; \text{ i} = 1, \ldots, \text{k.} \tag{1}$$

where a_i = ith value of the sub-criteria, a_{norm}= normalized value of sub-criteria, a_{min} = minimum value of sub-criteria, and a_{max}= maximum value of sub-criteria.

3. METHODS

3.1 Mixed-method approach

The mixed-method approach is a technique that combines quantitative and qualitative aspects of different parameters through a systematic approach or concept. It combines methodological approaches considering their fundamental aspects. As a value addition process, they can address the problem by considering various viewpoints so that a proper comprehension of the problem assessment is achieved. For the last couple of decades, the use of mixed-method research has increased considerably (Creswell, 2006) and has motivated researchers to move beyond the argument between quantitative and qualitative techniques (Morgan, 2007). Despite its usefulness, it poses a serious challenge, such as how to design overall methodology, whether both quantitative and qualitative methods are to be given equal priority or to be used concurrently or sequentially, and how to integrate them. Thus, keeping given the above mention aspects, the present study has primarily focused on the overall design and interactions of both the quantitative and qualitative methods.

The present study is motivated by the designs proposed by Leech and Onwuegbuzie (2009). Initially, a sequential mixed-method design has been considered, but there has been difficulty in having proper elucidation about the objective of the study, therefore concurrent triangulation mixed-method approach has been considered. The aim has been to rely on the outcomes of the quantitative method and use of qualitative assessment techniques to supplement and complement it by validating the assessment process.

Thereby, allowing us to improve our assessment objective (Leal et al., 2018). In the present study, a novel concurrent triangulation design of mixed methods research (MMR) has been proposed, for exploring and ascertaining important indicators by considering ex-post evaluation conditions for newly constructed all-weather rural roads. It integrates both qualitative and quantitative assessment approaches, which provide a complete understanding of the integrated effects that can yield generalized outcomes when applied for a real-life application.

Considering the advantages and limitations, the present study employs the PCA and fuzzy-MCDM techniques. PCA is based on the linear correlation of the data set. However, there are possibilities that data may not be correlated to substantiate the results of the PCA fuzzy-MCDM technique, which is based on relative importance. In the present study, PCA which considers quantitative assessment is compared with fuzzy-MCDM which contemplates qualitative assessment. The study procedure is outlined as under i) all the criteria and sub-criteria that define socio-economic impact status are selected after the consultation with researchers, policymakers, reviewing literature and by conducting the preliminary survey, ii) rural (PMGSY) road stretches for the study are identified, iii) data for the study is collected by preparing structured questionnaire through focus group survey, iv) the assessment of data using PCA technique coupled with fuzzy-TOPSIS is performed, and v) finally significant criteria and sub-criteria based on their variance and relative importance are ascertained.

3.2 Principal component analysis

The principal component analysis is a simple eigenvector-based multivariate analysis technique that stipulates anomalies associated with the studies incorporating several variables. It explains the internal structure of data by revealing the variance in the dataset (Harris, 1997). It identifies inputs of each variable to the components (factor loadings) for a given set of data. The main objective is to have an optimum linear combination, where primary criteria explain variability in the data set (Jolliffe, 2002). Mathematically, the PCA technique creates components where every component is a linear weighted combination of primary criteria as given in *Equation 2*:

$$\begin{aligned} PC_1 &= X_1 \times a_1 + X_2 \times a_2 + ... + X_n \times a_n \\ PC_m &= X_{m1} \times a_{m1} + X_{m2} \times a_{m2} + ... + X_{mn} \times a_{mn} \end{aligned} \quad (2)$$

where X_{m1} represents the amplitude of m^{th} principal component of the n^{th} criteria. The "factor scores" from the model are recovered by modifying the structure inferred by *Equation 2*. It yields a set of measures for every m principal component: (n = 1, ..., N). The eigenvalue analogs to the eigenvector represent variance (v) for every principal component. The components are arranged according to their variance such that the first principal component (PC_1) elucidates the maximal possible extent of variation. It considers the limitation that the summation of the squared amplitudes equals one (i.e., $X_{12}+ X_{22}+...+ X_{n2} = 1$). The amount of variance accounted by every single component to the total variation in the original data set is given as i/n. It is the summation of the eigenvalues and is equivalent to the total number of criteria in the original dataset (Kent, Bibby, & Mardia, 2006; Srinivas, Singh, & Sharma, 2017).

3.3 Fuzzy-TOPSIS for ranking the indicators

The study employs PCA for identifying key indicators based on their variance. But inter-correlation between sub-criteria is indistinct. This necessitates identifying key sub-criteria by accounting for their relative importance (ranks) and is achieved by employing analytical techniques. Cross-correlation, step-wise approach, multi-criteria techniques like the analytical hierarchy process (AHP), fuzzy AHP, and fuzzy-TOPSIS are some of the well-known analytical techniques (Singh et al., 2017). However, this study applies the fuzzy-TOPSIS approach to identify the key criteria by ranking them. It accounts for the change in satisfaction level before and after the deliverance of rural roads.

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is one of the recognized ranking techniques among other MCDM methods and has been first considered by (Hwang, Lai, & Liu, 1993; Hwang & Yoon, 1981). The hypothesis of the TOPSIS methodology is to identify the ideal and nadir solutions (Liang, 1999) and is based on the logic of comparative proximity.

It is observed as the distance of the sub-criteria to the ideal (nadir) point, which are to be ranked based on their priority. In the present study, the collected data is based on human perception and judgments which exhibits fuzziness. To overcome the fuzziness (uncertainty) associated with the data, the concept of fuzzy set theory has been integrated with the TOPSIS technique. This comprehensively facilitates the assessment of SEIA. The methodology followed for the study is shown in *Figure 3*.

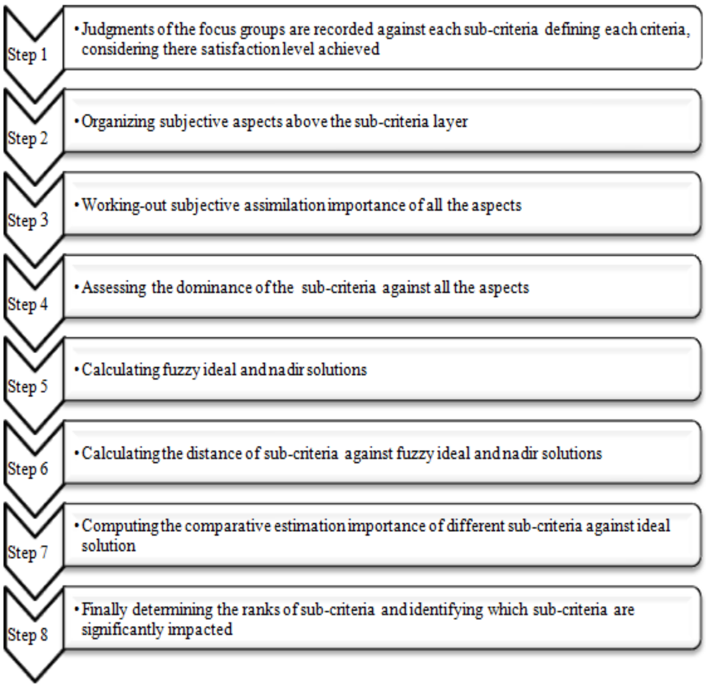

Figure 3. The methodical procedure followed in fuzzy-TOPSIS

The complete procedures for PCA and fuzzy-Topsis analysis employed in the present study are illustrated in Appendix I.

4. RESULT AND DISCUSSION

4.1 Principal component analysis interpretation

The study retains 10 PCs which are responsible for a total variance of 88.85%. The scree plot (*Figure 4*) assists to identify relevant components that are to be retained for further analysis. All components with eigenvalues greater than one are generally retained. To support this, the Monte Carlo PCA tool has also been applied parallelly. It calculates eigenvalues within the specified boundary condition, which are to be compared with eigenvalues obtained from PCA. In the current study, it is observed that the first component accounts for 15.213% of the total variance, and the remaining 9 PCs constitute about 73.64% of the total variability as shown in *Table 2*.

Table 2. Percentage variability and cumulative variability by the components

Components observing the SEIA sub-criteria	Eigenvalues	% of variance	Cumulative %
1	5.020	15.213	15.213
2	4.756	14.412	29.625
3	3.924	11.889	41.514
4	3.535	10.712	52.226
5	2.670	8.091	60.317
6	2.538	7.690	68.007
7	2.212	6.702	74.709
8	1.907	5.778	80.487
9	1.507	4.567	85.055
10	1.252	3.794	88.849

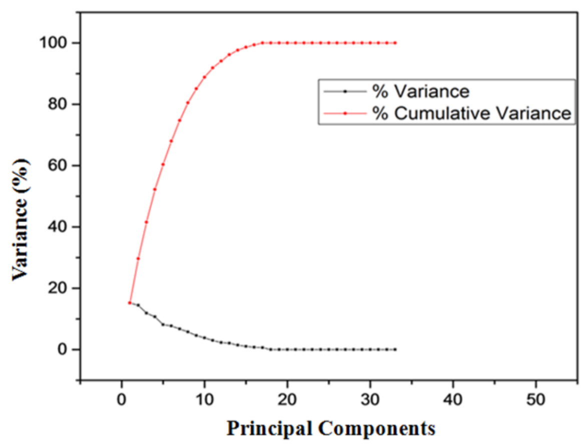

Figure 4. Scree plot depicting the proportion of variance vs principal components

The rotated component matrix (*Table 3*) is the key output obtained from PCA; it exhibits the correlation score of different sub-criteria for retained components. The loading score of each sub-criterion for a given component is illustrated in *Table 3*. This depicts that after the construction of PMGSY roads there has been a substantial change in these sub-criteria. The first component is contributed by higher loadings of sub-criteria such as agriculture self-employed (ISA), frequency of public transportation (PUBF), percent of male (EMAS), and female (EFAS) children attending school. The higher loading of sub-criterion ISA represents that there is a possible increase in dependency of rural inhabitants on agriculture due to the availability of resources as well as enhanced physical access to the nearest markets. It can also be induced that it may be due to decreased transportation and production cost of agricultural produce.

Moreover, higher loading of sub-criteria EMAS followed by EFAS depicts increased accessibility to the schools along with a considerable reduction in travel time to reach them. Travel time plays a significant role in the case of female students, which increases their possibility to attend school. Similarly, positive changes such as an increase in the number of public transportation units (PUBTU) along with the mid-core change in the cost of travel incurred by public transportation (PUBTC) are observed. This is obvious from their loadings contributing to the second PC. Consequently, it is also observed that the sub-criteria, viz., QSGOV, QL, QTVO contributing to the quality of neighbourhood (social environment) indicator show higher loadings. This depicts that there has been a substantial change in the living and social conditions of inhabitants. Moreover, the loadings of these sub-criteria also represent that possible positive change in the liveability conditions of inhabitants within the community enables them to involve in social gatherings. It also reflects a positive change in the quality of life of marginal groups (especially women).

However, along with the positives changes experienced due to developmental work, the analysis also indicates that there is no change in the condition of some of the sub-criteria (e.g. HTT), which is evident from their lower loadings (*Table 3*). The lower loadings score in the case of sub-criteria travel time to reach the health facility is probably because no subsequent change has been observed in the travel time to reach the health facility available to the inhabitants even after road construction. The possible reason is that the inhabitants are trying to avail of better/appropriate treatment facilities, which may even need a longer distance to be commuted.

Table 3. Rotated component matrix

Sub-criteria	Components									
	1	2	3	4	5	6	7	8	9	10
PUBF	-0.861	-	-	-	-	-	-	-	-	-0.332
ISA	0.849	-	-	-	-	-	-	-	-	-
EMAS	0.811	-	0.361	-	-	-	-	-	-	-
EFAS	0.788	-	-	-	-	-	-0.327	-	-	-
PVTTC	0.593	-	-0.363	-	-	-0.558	-	-	-	-
TTPUB	-0.501	-	0.328	0.402	-	-	-0.336	-	0.480	-
PUBTU	-	0.903	-	-	-	-	-	-	-	-
PUBTC	-	0.806	-	-	-	-	-	-	-	-
HAM	-	-0.778	-	-	-	-	-	-	-	-
EFLR	-	-	0.912	-	-	-	-	-	-	-
IWA	-	-	0.819	-	-	-	-	-	-0.330	-
EAM	-	-	-0.583	-0.560	-	-	0.411	-	-	-
II	-	-	-	0.936	-	-	-	-	-	-
HCA	-	-	-	0.739	-	-	-	-	-	-

QTVO	-	-	-	-	-0.792	-	-	-	0.473	-
ETT	-	-	-0.374	-	-0.728	-	-	-	-	-
IUA	-	-	-	-	-0.723	-	-	-	-	-
QSGIV	-	-	-	-	0.551	0.515	-	-	-	-
QPPO	0.491	-	-	-	0.532	-	-	-0.416	-	-
QL	-	-	-	-	-	0.812	-	-	-	-
QSGOV	-	-	-	-	-	0.510	-	0.397	-	-
PRISA	-	-	-	-	-	-	0.874	-	-	-
IUNA	-	-	-	0.508	-	-	-0.613	-	-	-
PRESA	-	-	0.482	-	-	0.333	0.599	-	-	-
EMLR	-	-	-	-	-	-	-	0.851	-	-
HFU	-	-	-	0.331	-	-	-	0.818	-	-
HTT	-	-0.362	-	-	-	-0.437	-	-0.449	-	-
HSANT	-	-0.446	-	-	-	-	-	-	0.732	-
HI	-	-	-	-0.339	-	-	-	-	0.712	-
IL	-	-	0.459	0.360	-	-	-	-	-0.468	0.446
TTPVT	-	-0.489	-	-	-	-	-	-	-	0.749
PHCA	-	-0.317	-	-	0.485	-0.306	-	-	-	0.605
PVTTU	0.442	-	0.308	-	-	-0.316	-	-	-	0.585

A 2-dimensional monoplot represents a component loading as the coefficients of the two principal components as shown in *Figure 5*. It assists in visualizing the interrelationships among the sub-criteria. A positive correlation is indicated when the vectors representing the sub-criteria pointing away from the origin of the monoplot are in the same direction. A negative correlation is observed when they are at 180˚angle to each other. From the first quadrant of the monoplot of *Figure 5*, the criteria, viz., access to the mode of transport for health facility (HAM), travel time to reach health centres (HTT), availability of primary health care center (PHCA) have a positive correlation with each other. The monoplot also represents the type of correlation among sub-criteria.

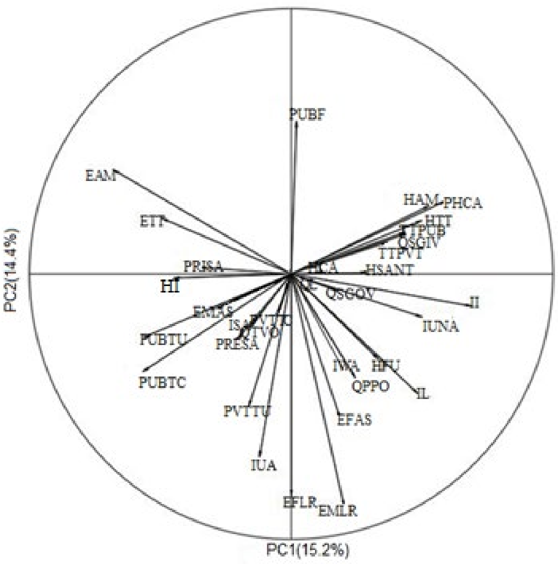

Figure 5. Monoplot representing the correlation

4.2 Fuzzy-TOPSIS findings

To have enhanced comprehension in supplementary to PCA about the status of the sub-criteria, the sub-criteria are ranked based on the comparative satisfaction level of rural inhabitants. The fuzzy-TOPSIS approach is employed to elucidate the most significant one. The study evaluates the most substantial sub-criteria and ranks them based on their relative importance. *Table 4* represents the ranks obtained by the sub-criteria based on the perceptions of the focus groups for the selected habitations.

Table 4. The Rank of sub-criteria concerning comparative estimate (CE*)

Sub-criteria	CE*	Rank	Sub-criteria	CE*	Rank
HFU	0.5011	1	PUBF	0.4349	18
EMAS	0.4921	2	PRESA	0.4345	19
EFAS	0.4832	3	EMLR	0.4325	20
QPPO	0.4767	4	QSGIV	0.4325	21
EFLR	0.4719	5	HAM	0.4319	22
ISA	0.4711	6	EAM	0.4324	23
QTVO	0.4693	7	TTPVT	0.4303	24
PUBTC	0.4658	8	PVTTU	0.4287	25
QL	0.4640	9	IWA	0.4241	26
II	0.4504	10	HTT	0.4204	27
QSGOV	0.4492	11	HSANT	0.4168	28
PUBTU	0.4471	12	PRISA	0.4161	29
IUA	0.4423	13	IUNA	0.4077	30
HI	0.4405	14	HCA	0.4022	31
TTPUB	0.4396	15	IL	0.4004	32
ETT	0.4381	16	PHCA	0.3947	33
PVTTC	0.4353	17			

It has been observed from the above evaluation that the sub-criteria contributing to health facility (e.g. use of health facility (HFU)), and sub-criteria contributing to education facility (percent of female children attending school (EFAS), literacy rate of female (EFLR), literacy rate of male (EMLR)) are ranked the most significant. There has been a significant change in these sub-criteria because of a possible reduction in travel time and the ability of female students to avail education facility with ease, which is also apparent from PCA analysis. These are followed by the sub-criteria contributing to the quality of neighbourhood (social environment) (i. e., QTVO, QL, and QSGOV) and Transport facility (i.e., TTPUB, PUBTC, and PVTTC). A similar pattern is also observed in the case of the sub-criteria contributing to income status criteria (i.e., HI, IUA). Furthermore, from the analysis, it has also been inferred that the sub-criteria contributing to a health facility (i.e., availability of clinic (HCA), availability of primary health Centre (PHCA), travel time to reach health facility (HTT)) have gained lower ranks, which depicts inhabitant's dissatisfaction towards these sub-criteria.

This is also observed in the case of the sub-criteria (i.e., IL, IUNA, IWA) contributing to income status indicator, which depicts little to no change in the status of these sub-criteria which substantiates our analysis done using PCA.

From the results of the overall analysis (i.e., PCA and fuzzy TOPSIS) it has been observed that results of PCA substantiate the findings of fuzzy TOPSIS. For example, the education facility criteria show significant impact and can be perceived from both the variance and relative importance of the sub-criteria contributing to it. This possible impact usually refers to a reduction in travel time. Because of this reduction in travel time, there has been an increase in the percentage of both male and female students attending schools. It can also be observed from the improved literacy rate of females. Further, the analysis also shows a positive change in travel conditions and economic growth which is well observed from the variance and relative importance of the sub-criteria contributing to the quality of neighbourhood criteria. But the investigation also shows that no significant change has been observed in the condition of the health facility criteria.

5. CONCLUSION

Assessment of socio-economic impacts instigated by the deliverance of rural roads is of prime importance from viewpoint of sustainable rural development. It reveals necessary knowledge about the potential socio-economic and cultural impacts on the lives of rural habitants and their communities. It assists concerned decision-makers in finding ways to mitigate or prevent adverse or insignificant impacts from happening. Moreover, it also emphasizes maximizing beneficial impacts, achieved by the provision of the planned forum. SEIA involves several criteria (i.e., qualitative and quantitative) and their interdependencies. Thus, ascertaining and exploring them creates a need for a systematic tool so that comprehensive assessment can be achieved at the regional level. Although, the literature suggests several techniques (experimental and quasi-experimental), yet they lag to accommodate the problem of biases arising from real-life data.

Considering this, the present study proposes a novel mixed-method approach that integrates multivariate analysis with the fuzzy MCDM technique. Here, the PCA considers quantitative data whereas fuzzy-TOPSIS accounts for qualitative data. The proposed approach accommodates the advantages of mixed-method design like its ability to attain any kind of changes according to the necessity of the study to be conducted. As a value addition, it increases the reliability of SEIA methodology. It deepens the understanding of SEIs to be perceived by decision-makers and stakeholders with ease. From the analysis of the present study, it is revealed that the PMGSY roads have contributed significantly to the upliftment of rural life. It shows that there has been a positive change in the education facility criteria. This can be observed from both the variance and relative importance of the sub-criteria contributing to it. This possible change is due to a reduction in travel time. Because of this reduction in travel time, there has been a positive impact in the form of an increase in the percentage of both male and female students attending schools as they can avail of education facilities with ease using better connectivity. Also, it is observed that the literacy rate of females has been improved significantly. Further, from the analysis, it can be concluded that the construction of PMGSY roads influenced travel conditions and economic growth progressively. This is well perceived from the change in the livability condition of the rural population along with sub-criteria contributing to the quality of neighbourhood criteria. But the investigation also shows that no significant change has been observed in the condition of the health facility criteria. This also is the case of diversification of rural livelihood conditions. Therefore, considering the policy implication the study points out that the concerned decision-makers are required to take necessary initiatives. These action plans/initiatives should be focused on promoting non-farm activities to foster livelihood diversification and making the rural population self-sustainable. Moreover, there is a need for proper distribution of health and education facilities available to rural inhabitants, which is important from viewpoint of overall rural development.

From the future scope of the study, the research can target the left-out areas (i.e., negative and continuing impacts, environmental (biophysical) impacts) which are to be incorporated in the SEIA.

APPENDIX I

The complete procedures for PCA and fuzzy-Topsis analysis employed in the present study are illustrated as below:

PCA analysis

The assessment of PCA is explained through two steps. In this study, PCA analysis has been performed using SPSS (statistical package for the social sciences) and mono plots have been drawn using 'Analyse it-2016' software. The step-wise process of PCA is as explained below.

Step 1: Data Processing

The data points corresponding to 33 sub-criteria have been gathered through focus-group discussions for every selected habitation.

- These collected data points are used as input for (PCA). Before the analysis is performed, the data gathered through the focus group panel is made consistent enough on a scale of 0 to 1.
- In the present study, KMO and Bartlett's Tests have been performed to identify sample adequacy. The Kaiser-Meyer-Olkin measures the adequacy of the sample. It varies between 0 and 1. It is considered better if the value is closer to 1. Bartlett's Test of Sphericity is based on the null hypothesis and used to check the statistical significance of the interrelation between the variable.
- Normally, $0 < KMO < 1$, if $KMO > 0.5$, the sample is adequate. Herein the value of KMO = 0. 873, which indicates the data sample is adequate and PCA can be performed.
- Further, 95% level of Significance, $\alpha = 0.05$, the p-value (Sig.) obtained is $0.000 < 0.05$, therefore the sample data is valid.
- Further, employing SPSS the eigenvalues and the corresponding eigenvectors for the data set are evaluated, which help determine the variance in data set caused by criteria in terms of principal components.
- It is observed that cumulative percent variance (88.85%) is contributed by the first 10 components.

Step 2: PCA Interpretation

PCA outputs are tabulated as factor scores or in the form of sub-criteria weights. Component loading measures the extent of proximity between principal components and sub-criteria, largest the loading either positive or negative represents the significance of the component. Positive loading depicts that the input of sub-criteria augments with the increase in loading of the component, and negative represents reduction. Moreover, sub-criteria with positive loading/weight signify a higher score whereas those with negative a lower score.

Fuzzy-TOPSIS approach

The data processor of the fuzzy-TOPSIS approach applied for the study herein as follows:

Step 1: The first step is to identify the important sub-criteria defining criteria, employed in SEIA. They are assessed based on the satisfaction level achieved by the rural inhabitants. The study considers two aspects, viz., satisfaction level 1(SL_1) (before) and satisfaction level 2 (SL_2) (after).
The aspects are positive and represent the satisfaction level of inhabitants before and after the construction of PMGSY roads.
Step 2: Next step is to calculate the comparative importance weights of the aspects. A pair-wise comparison matrix is developed. The study employs a fuzzy analytic hierarchy process (FAHP) approach to acquire the integrated weights for further assessment. Below is the pair-wise comparison matrix for two aspects considered, as shown below in *Table A.I.1*.

Table A.I.1. Fuzzy pair-wise comparison matrix of aspects

	SL_1			SL_2		
SL_1	1.00	1.00	2.00	0.20	0.25	0.33
SL_2	4.00	5.00	6.00	1.00	1.00	2.00

In the present study, the fuzzy synthetic approach is applied to assess the weights of the aspects, by employing *Equation A.I.2*. $\tilde{W}_i$ (where i = 1, 2, …, m) are normalized fuzzy numbers, with an intermediate value corresponds to 1. Fuzzy weights of the aspects obtained for the study are shown below in *Table A.I.2*. Further, the weights are defuzzified by the application of the geometric mean integration representation approach (GMIR) (Chen & Hsieh, 2000). For a given triangular fuzzy number (TFN), the defuzzified weight is calculated by employing the GMIR approach by employing *Equation A.I.1*. The calculated weights are normalized, which are given in *Table A.I.2*.

$$r(a) = \frac{a_1 + 4a_2 + a_3}{6} \quad \text{(A.I.1)}$$

where $\tilde{a} = (a_1, a_2, a_3)$ be the triangular fuzzy number.

$$\tilde{W}_i = \sum_1^m \tilde{a}_{ij} \otimes \left[\sum_{q=1}^m \sum_{r=1}^m \tilde{a}_{qr}\right]^{-1}, \text{ i = 1, …, m.} \quad \text{(A.I.2)}$$

Table A.I.2. Fuzzy weights for aspect SL1 and SL2

Fuzzy weights			
SL_1	0.12	0.17	0.38
SL_2	0.48	0.83	1.29

Table A.I.3. Defuzzified and normalized weights of aspects

	SL_1	SL_2
Defuzzified weights	0.20	0.85
Normalized Weight	0.18	0.81

Step 3: The next step in the process is to evaluate the dominance of the sub-criteria with respective aspects. These are acquired by using perception ratings mentioned in linguistic terms, by the focus groups. The mean dominance rating for every sub-criterion is assessed by employing the arithmetic mean approach. *Table A.I.4* shows the dominance of sub-criteria with respective aspects SL_1 and SL_2.

Let, D_{ic}^{f} = (C_{ic}^{f}, A_{ic}^{f}, B_{ic}^{f}) is the fuzzy dominance rating of the i^{th} sub-criteria about the c^{th} subjective aspect, evaluated by the f^{th} focus group, where (i = 1, …., m; c = 1, …, p; f = 1, …, n). The mean fuzzy dominance rating of the i^{th} sub-criteria about the c^{th} subjective aspect evaluated by the f^{th} focus-group is evaluated as given below:

$$\left[\frac{\left(\sum_{f=1}^{n} C_{ic}^{f}\right)}{n}, \frac{\left(\sum_{f=1}^{n} A_{ic}^{f}\right)}{n}, \frac{\left(\sum_{f=1}^{n} B_{ic}^{f}\right)}{n}\right]$$

Table A.I.4. The dominance of sub-criteria V/s aspects (SL_1) and (SL_2)

Sub-criteria	Fuzzy dominance ratings (SL_1)			Fuzzy dominance ratings (SL_2)		
	C	A	B	C	A	B
TTPUB	1.37	2.26	3.26	2.16	3.16	4.16
TTPVT	1.37	2.16	3.21	2.00	2.95	3.95
PUBTU	1.53	2.37	3.37	2.32	3.32	4.32
PVTTU	1.42	2.21	3.21	1.95	2.89	3.95
PUBF	1.47	2.32	3.32	2.05	3.05	4.05
PUBTC	1.63	2.58	3.58	2.74	3.74	4.74
PVTTC	1.32	2.21	3.21	2.11	3.05	4.05
II	1.79	2.74	3.74	2.37	3.37	4.37
HI	1.58	2.47	3.47	2.21	3.11	4.21
ISA	1.95	2.95	3.95	2.84	3.84	4.84
IWA	1.16	1.95	2.95	1.84	2.84	3.84
IL	1.16	1.84	2.84	1.42	2.32	3.32
IUA	1.42	2.37	3.37	2.21	3.21	4.21
IUNA	1.32	2.05	3.05	1.63	2.42	3.47
HFU	2.42	3.42	4.42	3.63	4.63	5.63
HCA	1.21	1.58	2.58	1.47	2.37	3.37
PHCA	1.16	1.53	2.53	1.32	2.21	3.21
HAM	1.26	2.11	3.11	2.00	3.00	4.00
HTT	1.16	1.95	2.95	1.84	2.74	3.74
HSANT	1.21	1.95	2.95	1.68	2.68	3.68
EMLR	1.42	2.32	3.32	2.00	3.00	4.00
EFLR	2.26	3.26	4.26	2.84	3.84	4.84
EMAS	2.37	3.37	4.37	3.37	4.37	5.37
EFAS	1.79	2.63	3.63	2.89	3.68	4.89
EAM	1.42	2.26	3.26	2.00	3.00	4.00
ETT	1.47	2.37	3.37	2.16	3.11	4.11
PRESA	1.47	2.32	3.32	2.16	3.00	4.00
PRISA	1.37	2.16	3.16	1.74	2.63	3.63
QPPO	1.68	2.68	3.68	3.00	4.00	5.00
QTVO	1.84	2.84	3.84	3.16	4.16	5.16
QL	1.74	2.74	3.74	2.68	3.68	4.68
QSGIV	1.37	2.32	3.32	2.00	3.00	4.00
QSGOV	1.42	2.32	3.32	2.37	3.37	4.37

Step 4: In this step, ideal and nadir solutions are computed. The ideal and nadir solutions are established on the hypothesis of comparative proximity. They are observed as the distance of sub-criteria *i* to the ideal (nadir) solutions and are ranked accordingly (Liang, 1999). As all the sub-criteria are positive, the standardized fuzzy dominance rating D_{ij} (max) of the i^{th} sub-criteria for aspect *j* is evaluated as shown in *Equation A.I.3*, where Δ_j = max (B_{ij}).

$$D_{ij} = \left(l_{ij}, m_{ij}, k_{ij}\right) = \left[\frac{C_{ij}}{\Delta_j}, \frac{A_{ij}}{\Delta_j}, \frac{B_{ij}}{\Delta_j}\right] \quad \text{(A.I.3)}$$

Table A.I.5 illustrates the standardized dominance ratings of sub-criteria obtained with respect to aspects SL_1 and SL_2.

Table A.I.5. Standardize dominance rating of sub-criteria V/s aspects (SL_1) and (SL_2)

Sub-criteria	Fuzzy dominance ratings (SL_1)			Fuzzy dominance ratings (SL_2)		
	C	A	B	C	A	B
TTPUB	0.31	0.51	0.74	0.38	0.56	0.74
TTPVT	0.31	0.49	0.73	0.36	0.52	0.70
PUBTU	0.35	0.54	0.76	0.41	0.59	0.77
PVTTU	0.32	0.50	0.73	0.35	0.51	0.70
PUBF	0.33	0.52	0.75	0.36	0.54	0.72
PUBTC	0.37	0.58	0.81	0.49	0.66	0.84
PVTTC	0.30	0.50	0.73	0.37	0.54	0.72
II	0.40	0.62	0.85	0.42	0.60	0.78
HI	0.36	0.56	0.79	0.39	0.55	0.75
ISA	0.44	0.67	0.89	0.50	0.68	0.86
IWA	0.26	0.44	0.67	0.33	0.50	0.68
IL	0.26	0.42	0.64	0.25	0.41	0.59
IUA	0.32	0.54	0.76	0.39	0.57	0.75
IUNA	0.30	0.46	0.69	0.29	0.43	0.62
HFU	0.55	0.77	1.00	0.64	0.82	1.00
HCA	0.27	0.36	0.58	0.26	0.42	0.60
PHCA	0.26	0.35	0.57	0.23	0.39	0.57
HAM	0.29	0.48	0.70	0.36	0.53	0.71
HTT	0.26	0.44	0.67	0.33	0.49	0.66
HSANT	0.27	0.44	0.67	0.30	0.48	0.65
EMLR	0.32	0.52	0.75	0.36	0.53	0.71
EFLR	0.51	0.74	0.96	0.50	0.68	0.86
EMAS	0.54	0.76	0.99	0.60	0.78	0.95
EFAS	0.40	0.60	0.82	0.51	0.65	0.87
EAM	0.32	0.51	0.74	0.36	0.53	0.71
ETT	0.33	0.54	0.76	0.38	0.55	0.73
PRESA	0.33	0.52	0.75	0.38	0.53	0.71
PRISA	0.31	0.49	0.71	0.31	0.47	0.64
QPPO	0.38	0.61	0.83	0.53	0.71	0.89
QTVO	0.42	0.64	0.87	0.56	0.74	0.92
QL	0.39	0.62	0.85	0.48	0.65	0.83
QSGIV	0.31	0.52	0.75	0.36	0.53	0.71

QSGOV	0.32	0.52	0.75	0.42	0.60	0.78

Further, the fuzzy ideal and nadir solutions for sub-criteria with respect to aspects SL_1 and SL_2 are computed for representation values r (D_{ij}), by employing the GMIR approach. The fuzzy ideal and nadir solutions are defined as; Fuzzy ideal solution (I) = ($D_1^+, D_2^+, \ldots, D_j^+, \ldots, D_c^+$) and nadir solution as (N) = ($D_1^-, D_2^-, \ldots, D_j^-, \ldots, D_c^-$). *Table A.I.6* shows the fuzzy ideal and nadir ratings obtained.

Table A.I.6. Fuzzy ideal and nadir values for sub-criteria with respect to aspects (SL1 and SL2)

Aspects	Fuzzy Ideal values			Fuzzy Nadir values		
SL_1	0.55	0.77	1.00	0.23	0.23	0.45
SL_2	0.65	0.83	1.00	0.17	0.17	0.35

Step 5: Evaluating sub-criteria distances with reference to fuzzy ideal and nadir solutions using *Equation A.I.4* and *Equation A.I.5*. *Table A.I.7* depicts the distance of sub-criteria with reference to fuzzy ideal and nadir solutions.

$$d_i^+ = \sqrt{\sum_{j=1}^{C}\left[\left(\beta_j\right)^2 \times \left(\alpha_M \times \left(D_j^+, D_{ij}\right)\right)^2\right]} \quad \text{(A.I.4)}$$

$$d_i^- = \sqrt{\sum_{j=1}^{C}\left[\left(\beta_j\right)^2 \times \left(\alpha_M \times \left(D_j^-, D_{ij}\right)\right)^2\right]} \quad \text{(A.I.5)}$$

where $i = 1, 2, \ldots, k$.

Step 6: Final step is to assess the rank of sub-criteria with respect to comparative estimates with an ideal solution (for the present study). The comparative estimate (CE^*) for the ideal solution is assessed by employing *Equation A.I.6*. *Table A.I.8* depicts the rank of sub-criteria for a comparative estimate.

$$CE_i^* = \frac{d_i^-}{d_i^- + d_i^+} \quad \text{(A.I.6)}$$

Table A.I.7. The distance of sub-criteria v/s fuzzy ideal and nadir solutions

Sub-criteria	d_i^-	d_i^+	Sub-criteria	d_i^-	d_i^+
TTPUB	0.540	0.540	HAM	0.413	0.543
TTPVT	0.544	0.544	HTT	0.398	0.548
PUBTU	0.537	0.537	HSANT	0.394	0.551
PVTTU	0.544	0.544	EMLR	0.414	0.543
PUBF	0.542	0.542	EFLR	0.394	0.532
PUBTC	0.532	0.532	EMAS	0.515	0.531
PVTTC	0.542	0.542	EFAS	0.468	0.529
II	0.536	0.536	EAM	0.475	0.543
HI	0.538	0.538	ETT	0.421	0.540
ISA	0.532	0.532	PRESA	0.416	0.541
IWA	0.547	0.547	PRISA	0.392	0.551
IL	0.560	0.560	QPPO	0.484	0.531

IUA	0.539	0.539	QTVO	0.496	0.531
IUNA	0.554	0.554	QL	0.461	0.533
HFU	0.533	0.533	QSGIV	0.414	0.543
HCA	0.559	0.559	QSGOV	0.438	0.537
PHCA	0.564	0.564			

Table A.I.8. The Rank of sub-criteria with respect to comparative estimate (*CE**)

Sub-criteria	CE^*	Rank	Sub-criteria	CE^*	Rank
HFU	0.5011	1	PUBF	0.4349	18
EMAS	0.4921	2	PRESA	0.4345	19
EFAS	0.4832	3	EMLR	0.4325	20
QPPO	0.4767	4	QSGIV	0.4325	21
EFLR	0.4719	5	HAM	0.4319	22
ISA	0.4711	6	EAM	0.4324	23
QTVO	0.4693	7	TTPVT	0.4303	24
PUBTC	0.4658	8	PVTTU	0.4287	25
QL	0.4640	9	IWA	0.4241	26
II	0.4504	10	HTT	0.4204	27
QSGOV	0.4492	11	HSANT	0.4168	28
PUBTU	0.4471	12	PRISA	0.4161	29
IUA	0.4423	13	IUNA	0.4077	30
HI	0.4405	14	HCA	0.4022	31
TTPUB	0.4396	15	IL	0.4004	32
ETT	0.4381	16	PHCA	0.3947	33
PVTTC	0.4353	17			

APPENDIX II

Table A.II.1. The distribution of data representing the condition after the construction of rural roads

Criteria	Sub-criteria	Minimum	Mean	Maximum
	TTPUB	1.00	3.32	5.00
	TTPVT	2.00	3.63	5.00
Transport facility	PUBTU	1.00	3.58	5.00
	PVTTU	1.00	2.53	5.00
	PUBF	1.00	2.05	4.00
	PUBTC	2.00	3.89	5.00
	PVTTC	1.00	3.32	5.00
	II	2.00	2.79	4.00
	HI	2.00	3.21	5.00
	ISA	1.00	1.84	3.00
Income status	IWA	1.00	1.21	2.00
	IL	1.00	1.32	3.00
	IUA	2.00	2.95	4.00
	IUNA	2.00	3.00	4.00
	HFU	4.00	4.79	5.00
	HCA	1.00	1.42	2.00
	PHCA	1.00	1.21	2.00
Health facility	HAM	2.00	3.95	5.00
	HTT	1.00	3.26	5.00
	HSANT	2.00	3.21	4.00
	EMLR	2.00	3.16	4.00

	EFLR	2.00	2.63	4.00
	EMAS	4.00	4.68	5.00
Education facility	EFAS	3.00	4.48	5.00
	EAM	1.00	3.74	5.00
	ETT	1.00	2.21	5.00
	PRESA	1.00	1.47	2.00
	PRISA	1.00	1.74	2.00
	QPPO	2.00	4.42	5.00
	QTVO	2.00	4.21	5.00
Quality of neighbourhood	QL	2.00	2.42	4.00
	QSGIV	3.00	3.84	5.00
	QSGOV	2.00	3.37	4.00

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